Physica A 495 (2018) 211–214

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

A machine learning approach for predicting the relationship between energy resources and economic development

Dušan Cogoljević [a], Meysam Alizamir [b,*], Ivan Piljan [a], Tatjana Piljan [a], Katarina Prljić [c], Stefan Zimonjić [a]

[a] Faculty of Business Economics and Entrepreneurship, Mitropolita Petra 8, 11000 Belgrade, Serbia
[b] Young Researchers and Elite Club, Hamedan Branch, Islamic Azad University, Hamedan, Iran
[c] Faculty of Engineering, University of Kragujevac, Sestre Janjic 6,34000 Kragujevac, Serbia

HIGHLIGHTS

- In this investigation was analyzed the economic development prediction.
- Machine learning approach to predict economic development.
- Machine learning approach can be utilized in applications of economic development forecasting.

ARTICLE INFO

Article history:
Received 14 October 2017
Received in revised form 6 December 2017
Available online 21 December 2017

Keywords:
Economic development
Energy usage
Prediction

ABSTRACT

The linkage between energy resources and economic development is a topic of great interest. Research in this area is also motivated by contemporary concerns about global climate change, carbon emissions fluctuating crude oil prices, and the security of energy supply. The purpose of this research is to develop and apply the machine learning approach to predict gross domestic product (GDP) based on the mix of energy resources. Our results indicate that GDP predictive accuracy can be improved slightly by applying a machine learning approach.

1. Introduction

1.1. Overview of energy usage and economic development

Energy is essential to almost all social activities. Lack of access to reliable, affordable, and modern energy resources represents a constraint to economic and social progress in many parts of the world. In the last three decades, the effect of energy usage on economic growth has gained significant attention both at the national and international level, as discussed in reference [1]. Research in this area today is also motivated by contemporary concerns about global climate change, carbon emissions fluctuating crude oil prices, and the security of energy supply. The ability to establish patterns of association between energy resources and economic growth is of immense relevance for policy formulation.

Artificial neural networks (ANNs) and machine learning techniques have been applied to a variety of topics related to energy and economic development. Reference [2] introduced ANN as a statistical tool and econometric tool. Reference [3] studied the performances of an ANN for modeling electricity demand in Turkey and the results were very useful in

* Corresponding author.
E-mail address: meysamalizamir@gmail.com (M. Alizamir).

https://doi.org/10.1016/j.physa.2017.12.082

Table 1
Input and output parameters.

Index	Parameters	Min.	Max.
1.	Alternative and nuclear energy as a percentage of total energy use [%]	0.01	48.88
2.	Fossil fuel energy as a percentage of total energy use [%]	17.34	97.81
3.	Combustible renewables and waste as a percentage of total energy use [%]	0.58	31.21

guiding future studies. Since electricity plays a significant role in a country's energy usage profile and development policy, reference [4] applied an ANN model for electricity consumption, with results demonstrating that the model performs well. As sustainability requires an understanding the interaction of natural and human systems, reference [5] discussed the feasibility of using ANN to establish an adjustment prediction model for complex systems of sustainable development. Considering the dynamic links between renewable energy use and economic growth, reference [6] investigated the nonlinear causality between renewable energy consumption, economic growth as measured by gross domestic product (GDP), total energy consumption, and unemployment.

1.2. Objective

Although several studies have investigated the relationship between energy usage and GDP growth, the main goal of this research note is to apply a machine learning approach in order to address the high nonlinearity of the data. As a machine learning approach, ANN was used with two learning algorithms, extreme learning machine (ELM) and back propagation algorithm [see references [7–13]]. Since the used data has high nonlinearity, the ANN transforms the data in two groups where linear separation can be applied to the transformed data. In other words the ANN model handles the nonlinear pattern of the data. Linear regression models could be very time consuming and do not handle properly nonlinear data [14,15]. ANN models could be used in different architectures as can be seen for example in the following references [16,17].

2. Material and methods

2.1. Statistical data

We analyze the relationship between a country's energy resource mix and economic growth as measured by GDP. Table 1 shows the input parameters that were used in this analysis The World Bank Database was used as the data source. As the output parameter, the GDP growth rate (percentage) was used.

2.2. Artificial neural network

Artificial neural networks (ANN) are computational models that are based on connected units or neurons in some architecture. The neurons communicate among themselves by signals. Every neuron performs calculations based on defined training algorithms. In this analysis, we apply both the extreme learning machine (ELM) and back propagation learning algorithms.

The back propagation learning algorithm is the most common method for the training process of ANN models. This algorithm has two phases, propagation and updating of weights. In the first phase, the inputs are presented to the network and propagate forward through the network until the last layer. The obtained output of the network is compared with the desired output and the error value is computed in the last layer. The error value is then propagated backwards through the network in order to update the weights in the all neurons.

ELM was developed for neural networks with single hidden layer, as reported in references [10–12]. The ELM method can calculate results faster than traditional learning approaches because ELM avoids the iterative tuning of the parameters.

For M arbitrary samples $(\mathbf{x}_i, \mathbf{t}_i)$ where $\mathbf{x}_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^{\mathrm{T}} \in \mathbf{R}^n$ and $\mathbf{t}_i = [t_{i1}, t_{i2}, \ldots, t_{im}]^{\mathrm{T}} \in \mathbf{R}^m$, the neural network with N hidden nodes and activation function $g(x)$ can be modeled as follows [10–12]:

$$\sum_{i=i}^{N} \beta_i g_i\left(\mathbf{x}_j\right) = \sum_{i=i}^{N} \beta_i g\left(w_i \mathbf{x}_j + b_i\right) = o_{j.}\, j = 1, \ldots, N \tag{1}$$

where $w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^{\mathrm{T}}$ is the weight vector between input and hidden nodes, $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{in}]^{\mathrm{T}}$ is the weight vector between output and hidden nodes, and b_i is the threshold of the ith hidden node.

3. Results and discussion

The main parameters of the ELM and back propagation algorithms are presented in Table 2. In our analysis, 70% of the data was used for training and 30% of the data was used for testing. The predictive performance of the proposed models was

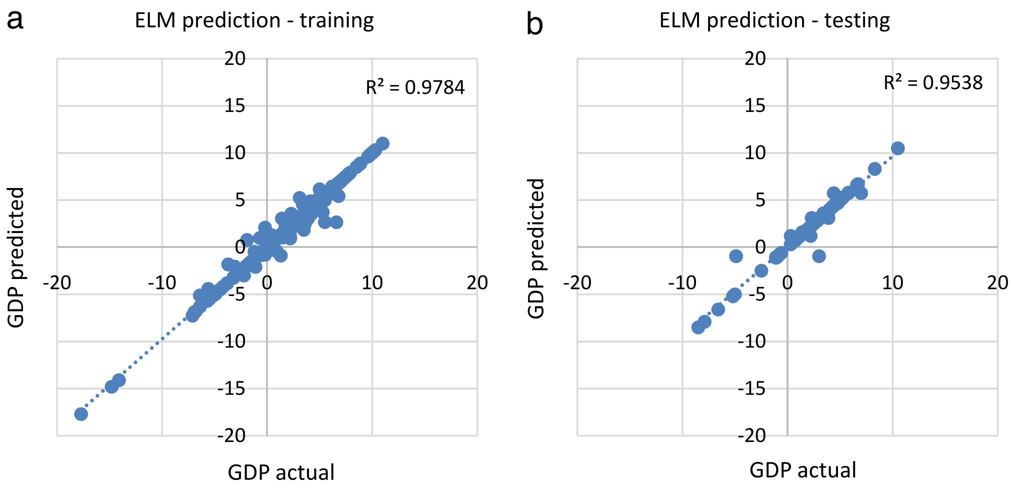

Fig. 1. ELM prediction of GDP in (a) Training and (b) Testing.

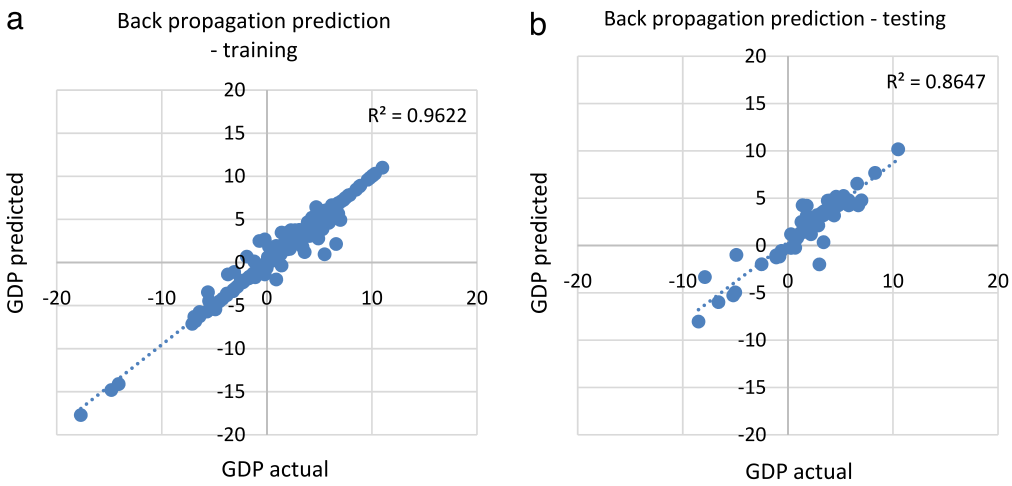

Fig. 2. Back propagation prediction of GDP in (a) Training and (b) Testing.

Table 2
ELM and back propagation parameters.

ELM		Back propagation	
Number of layers	3	Number of layers	3
Learning rule	ELM	Learning rule	Back propagation
RMSE – training	0.5827	RMSE – training	0.7702
RMSE – testing	0.7693	RMSE – testing	1.3213
R^2 – training	0.9784	R^2 – training	0.9622
R^2 – testing	0.9538	R^2 – testing	0.8647

compared in terms of the root means square error (RMSE) and coefficient of determination (R^2). As shown in Table 2, the ELM approach has higher predictive accuracy than the back propagation algorithm.

After several training processes, the average calculation time for the ELM algorithm was 300 s while the average calculation time for the back propagation algorithm was 400 s using the same hardware.

Figs. 1 and 2 shows the prediction of GDP in the training and testing phase for the ELM and back propagation algorithms, respectively. Based on an examination of the plots, we find that prediction of GDP by the ELM is slightly better than prediction than back propagation.

4. Conclusion

There is a great interest in the connection between the mix of energy resources and economic development, particularly in today's changing context. It is important for decision makers to understand these relationship patterns in order to design

effective energy and environmental policies. Building on previous research on artificial neural networks (ANN), we tested two learning algorithms. A machine learning approach was applied in order to address the high nonlinearity of the data and results were compared to those of a back propagation algorithm. Based on the results, ANN can be useful in analyzing the relationship between the mix of energy resources and economic growth and that it may be possible to improve predictive accuracy with the use of a machine learning approach.

References

[1] A.S. Alshehry, M. Belloumi, Energy consumption, carbon dioxide emissions and economic growth: The case of Saudi Arabia, Renew. Sustain. Energy Rev. 41 (2015) 237–247.
[2] A. Alonso-Rodriguez, Forecasting economic magnitudes with neural network models, Int. Adv. Econ. Res. 5 (2) (1999) 215–230.
[3] M. Kankal, E. Uzlu, Neural network approach with teaching–learning-based optimization for modeling and forecasting long-term electric energy demand in Turkey, Neural Comput. Appl. (2016) 1–11.
[4] Y.C. Hu, Electricity consumption prediction using a neural-network-based grey forecasting approach. Journal of the Operational Research Society, pp. 1–6.
[5] C. Shi, P. James, Z.Y. Guo, Application of artificial neural network in complex systems of regional sustainable development, Chin. Geogr. Sci. 14 (1) (2004) 1–8.
[6] M.B. Mbarek, I. Abdelkafi, R. Feki, Nonlinear causality between renewable energy, economic growth, and unemployment: Evidence from Tunisia, J. Knowl. Econ. (2016) 1–9.
[7] G.B Huang, Q.Y. Zhu, C.K. Siew, Extreme learning machine: A new learning scheme of feedforward neural networks, International Joint Conference on Neural Networks, vol. 2, 2004, pp. 985–990.
[8] D. Wang, G.B. Huang, Protein sequence classification using extreme learning machine, Proceedings of International Joint Conference on Neural Networks, vol. 3, 2005, pp. 1406–1411.
[9] G.B. Huang, Q.Y. Zhu, C.K. Siew, Real-Time Learning Capability of Neural Networks. Technical Report ICIS/45/2003, School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, 2003.
[10] R. Nian, B. He, B. Zheng, M.V. Heeswijk, Q. Yu, Y. Miche, et al., Extreme learning machine towards dynamic model hypothesis in fish ethology research, Neurocomputing 128 (2014) 273–284.
[11] G.B. Huang, Q.Y. Zhu, C.K. Siew, Extreme learning machine: Theory and applications, Neurocomputing 70 (2006a) 489–501.
[12] G.B. Huang, L. Chen, C.K. Siew, Universal approximation using incremental constructive feedforward networks with random hidden nodes, IEEE Trans. Neural Netw. 17 (2006b) 879–892.
[13] M. Mohammadhassani, H. Nezamabadi-Pour, M. Suhatril, M. Shariati, Identification of a suitable ANN architecture in predicting strain in tie section of concrete deep beams, Struct. Eng. Mech 46 (6) (2013) 853–868.
[14] F. Kemp, Applied multiple regression/correlation analysis for the behavioral sciences, J. Royal Stat. Soc.: Ser. D Stat. 52 (4) (2003) 691–691.
[15] C.H. Mason, W.D. Perreault Jr., Collinearity, power, and interpretation of multiple regression analysis, J. Mark. Res. (1991) 268–280.
[16] A. Toghroli, M. Mohammadhassani, M. Suhatril, M. Shariati, Z. Ibrahim, Prediction of shear capacity of channel shear connectors using the ANFIS model, Steel Compos. Struct. 17 (5) (2014) 623–639.
[17] M. Safa, M. Shariati, Z. Ibrahim, A. Toghroli, S.B. Baharom, N.M. Nor, D. Petkovic, Potential of adaptive neuro fuzzy inference system for evaluating the factors affecting steel-concrete composite beam's shear strength, Steel Compos. Struct. 21 (3) (2016) 679–688.